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Contested Chinese Dreams of AI? Public Discourse about Artificial Intelligence on WeChat and People's Daily Online

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Artificial intelligence (AI) has become a prominent public issue, particularly in China, where the government has announced plans to turn the country into a global AI power. This study analyses public discourse about AI in China through the conceptual lens of public spheres theory and counter-public spheres. It compares the official AI narrative on *People's Daily Online* with public discussion about AI on the social medium *WeChat*, where we assumed that official views would be challenged. Using a combination of qualitative and computational methods, 140,000 AI-related articles published between 2015 and 2018 were studied. Findings reveal that AI-related discourse on *WeChat* is surprisingly similar to that on *People's Daily Online*. That is, it is dominated by industry and political actors, such as government agencies and technology companies, and is mostly characterized by discussions about the economic potential of the technology, with strongly positive evaluations, and little critical debate.

Keywords: artificial intelligence, WeChat, science communication, public sphere, counter publics

1. Introduction

Since 2015, the Chinese Communist Party, led by President Xi Jinping, has promoted the 'Chinese Dream' (中国梦): the party's vision of turning China into a strong nation and a cyber-superpower (China Daily, 2015). As a step in realising this vision, the development of artificial intelligence (AI) sectors has been mandated by the ruling party, who have vowed to turn China into a global hub of AI innovation by 2030 (CSC, 2015; Deng, 2018).

Alongside its purported economic benefits (Rao et al., 2017), however, AI carries significant risks and challenges. For instance, it is estimated that over 50 percent of Chinese jobs may become automated in the future – an outcome that could affect over 390 million employees (Manyika et al., 2017: 9). Moreover, the government's potential use of AI for mass surveillance and automated weaponry is another common source of concern among researchers and commentators (Chen, 2018; Larson, 2018; Jacobs, 2018).

In this debate about state-fostered AI development in China, we wondered how the

Chinese public viewed the government's position. This speculation led to our research question: *To what extent do social media serve as a counter-public wherein the official narratives around China's national AI programs are challenged*? To address this question, our study interrogated the discursive contestation of AI on two platforms: *People's Daily Online* (*PD*) and *WeChat.*

As the online portal for the *People's Daily* – China's largest newspaper group (Liang, 2018) – *PD* broadcasts official messages from the central government. As a mouthpiece of the Central Committee of the Communist Party of China (CPC), its editorials and commentaries represent the official viewpoints of the Chinese authorities (Wu, 2014). *WeChat*, on the other hand, hosting over one billion active users monthly, is the most popular social media platform in China (Xinhua, 2018). It has over 12 million users on its 'public account platform' (公众账号平台) – a service that allows both individuals and organisations to publish articles[1] that are visible to all *WeChat* users (Xinhua, 2017). These public accounts now serve as a primary source of news and other forms of information for Chinese internet users (Yi & Cheng, 2015; Zhao, 2014).

To analyse AI discourse in China, we collected over 140,000 AI-related articles from *WeChat* and *PD* between 2015 and 2018. To examine these articles, we focused on three dimensions that were identified in prior analyses of debates about science-related issues in the public sphere: *standing*, *framing*, and *positioning* (Ferree et al., 2002; Schäfer, 2009; Gerhards & Schäfer, 2010). These three dimensions were adopted as the theoretical and analytical framework for our study. To operationalise this framework, we used a combination of qualitative analysis and computational methods, including topic modelling and sentiment analysis.

2. Conceptual Framework

2.1 Science and the public sphere

The public sphere has been conceptualized as a communicative sphere, in which matters of common concern are discussed and opinions formed, and where all proceedings are open to the public (cf. Schäfer, 2015). This concept of the public sphere

[1] *WeChat* articles published by public accounts have various styles. In most cases, they look like news articles or long blog posts.

has been advanced in political and communication theories over several decades (Habermas et al., 1974; Hauser, 1999; Keane, 1995), and has also been introduced to research in science and technology (Gauchat, 2012).

The Sociology of Science, Science and Technology Studies (STS), and other social-scientific analyses of science, have long argued that rhetoric and politics are constitutive of the scientific enterprise (Foucault, 1972; Latour, 1993; Mosco, 2004). Technologies are, according to Mosco (2004: 118), 'mutually constituted out of a culture that creates meaning and a political economy that empowers it.' In this context, the concept of the public sphere serves as a conceptual heuristic to interrogate the intersection between meaning creation and power contestation around science and technology.

Gerhards and Schäfer (2009) introduce the concept of the 'scientific public sphere' to discuss different models of public communication, wherein public opinion of, and societal reactions to science are constructed. They argue that in public spheres, different issues, including science and technology, are publicly discussed, and ultimately evaluated. These public discourses, and their resulting evaluations, influence the implementation of a given technology. In the public sphere, and particularly in mediated platforms such as news media or social media, different stakeholders can position their views on, and evaluations of a technology. In so doing, they endeavour to make their views pervasive, in order to legitimize or undermine the issue in question (Gerhards & Schäfer, 2009).

While Gerhards and Schäfer analyse Western democracies, their argument is not limited to democratic countries. For a single-party authoritarian country like China, garnering consent for science and technology projects is just as, if not more, necessary. Because the central government plans and finances China's major science and technology projects, the legitimacy of these projects is linked to the legitimacy of the ruling party. Thus, mainstream media, such as *PD*, often function as the party's communication apparatus to influence and guide public opinion (Zhao, 1998; Wu, 2014). In this way, the government exerts its hegemony over a considerable portion of the public sphere.

At the same time, this top-down hegemony can be challenged by dissenting voices from civil society (Yang & Calhoun, 2007) or grassroots activists (Kay, Zhao, & Sui, 2015). This bottom-up resistance can constitute *counter-public spheres* (Negt and Kluge, 1972;

Fraser, 1990; Downey & Fenton, 2003) – forms of collective expression that respond to, and potentially challenge mainstream public discourse (Downey & Fenton, 2003: 194). Counter-public spheres often emerge when this mainstream public discourse fails to provide a rational or critical discourse about an issue of common concern (Calhoun, 1993). As outlined by prior studies on China's public sphere, new information and communication technologies, and social media in particular, have contributed to the emergence of counter-public spheres in that country (Lee, So, & Leung, 2015; Sima, 2011; Rauchfleisch & Schäfer, 2015).

2.2 Analysing Public Debate

Several scholars have analysed media discourses around AI in recent years, mostly in Western countries. They point out that such discourses are often sensationalised (Goode, 2018), industry-driven (Elish and boyd, 2018), and politicized (Brennen et al., 2018). For instance, Elish and boyd's (2018) study on AI rhetoric reveals that the business community has manufactured an over-hyped vision of AI, by focusing on its potential and exaggerating its methodological capabilities. Similarly, Brennen et al. (2018), in news coverage of AI in the UK, detect a prevalence of industry concerns, such as concerns around products and initiatives. Our study adds to this scholarship.

In focusing on China, this study analysed an under-researched, yet highly relevant case. To understand public and counter-public spheres in China, we used a framework proposed by Ferree et al. (2002) and Gerhard and Schäfer (2009). In their analyses of abortion and biotechnology debate, they developed a conceptual framework to measure public debate around science and technology along three dimensions: *standing*, *framing*, and *positioning*.

- *Standing* measures the prevalence of different stakeholders in public discourse. In any given debate, the stronger a stakeholder's presence, the more influential s/he is likely to be (Ferree et al., 2002).
- *Framing* refers to the contextualization and interpretation of a topic. In public discourses around technology and science (and other issues), actors make sense of, and give meaning to an issue by using frames (Gamson & Modigliani, 1989). These frames entail the way an issue is viewed. For example, is it a political,

economic, legal, social, or other issue (Entman, 1993); is it seen as a problem; and what measures should be taken by responsible parties in relation to it (Gerhard and Schaefer, 2009: 441)?

- Building on Ferree et al.'s (2002) framework, Gerhards and Schäfer (2009) added *positioning* as a third dimension. *Positioning* describes the prevalence of different evaluations of a topic (Gerhard & Schäfer, 2009). For example, what is a stakeholder's position on an issue, and how is that position presented (i.e. positively or negatively) in the debate in general (Schäfer, 2007)?

We employed all three dimensions to analyse public discourses around AI in China. In our study, *PD* represents the authoritative realm where the party state's official narratives about AI are propagated. In contrast, *WeChat* represents a potential counter-public where multiple actors and narratives can coexist, and contest various issues. To assess to what extent the discussion around AI on *WeChat* serves as a 'counter-public sphere' that challenges the official discourses presented in *PD*, we compared both platforms. To this end, we asked the following questions:
RQ1 – *Standing*: How diverse is the spectrum of actors participating in AI debates on *WeChat*?

RQ2 – *Framing*: How does the framing around AI differ among actors on *WeChat*, and between *WeChat* and *PD*?

RQ3 – *Positioning*: How does sentiment about AI differ among actors on *WeChat*, and between *WeChat* and *PD*?

3. Methods

3.1 Data collection

As *WeChat* does not have application programming interfaces (APIs), we used a Selenium-based web crawler to retrieve articles published by its public accounts (Fu, 2018). The crawler visited, and sent the search query '□ □ □ □' ('artificial intelligence') to, a third-party search engine – sogou.com – where historical *WeChat* posts from public accounts are archived. Using the time filter function of Sogou, the crawler collected the 100 articles that were most relevant to the search term from each day of our study period: 1 January 2015 to 1 October 2018. The rationale behind setting 2015 as the starting point for the data collection was that the Chinese government launched its official AI agenda in that year. We terminated the crawler on 1 October 2018 to begin data analysis. Using another web crawler, we collected news articles from *PD's* online search engine – *search.people.com.cn* – using the same search keyword and timeframe. In total, we collected 128,343 *WeChat* articles and 20,666 *PD* articles.

3.2 Standing

We employed multi-step coding to identify the actors participating in public discourse surrounding AI on *WeChat*. We used a weighted sample of *WeChat* public profiles (n = 1,100) from the dataset, and manually annotated them based on information provided in them (i.e. each account's identity verification and function description). In the second step, we organized the labels used for this annotation into categories based on their interrelationship. Seven categories emerged from the data: 1) media organization; 2) tech company; 3) non-tech company; 4) academic; 5) government institution; 6) civil society; and 7) non-institutional account. A detailed codebook with examples is included in Appendix A.

For validation, a second coder coded a random subset of 110 user profiles, using the same codebook. Inter-coder reliability was calculated using Cohen's Kappa, and showed a high degree of agreement between coders (κ= .94).

3.3 Framing

To investigate the frames used to discuss AI, we employed a two-step procedure. The first step focused on identifying prevalent *topics* from both *WeChat* and *PD* using Latent Dirichlet Allocation (LDA) (Blei et al., 2003). Jieba toolkit (Qin & Wu, 2019) was used to generate tokenized versions of articles. We then adopted Maier et al.'s (2018) approach to further pre-process data, and validate different LDA models[2]. Based on the evaluation of topic words, sample articles, and interactive visualizations of LDA, we agreed on topic numbers (k) of 30 and 20 for the most interpretable models

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[2] This pre-processing step involved removing stop words, sparse terms, and dense terms. We trained LDA models with combinations of k (k = {10, 20, … ,80}) and hyper-parameter Alpha (alpha = {.005, .01, .05, .1, .2, .5, 1}). Beta was set at 1/k (Maier et al., 2018). For each k, we selected a model with the best topic coherence.

for *WeChat* and *PD*, respectively. After removing 'boilerplate' topics[3], 26 topics were eventually identified in the *WeChat* corpus and 17 in the *PD* corpus.

In the second step, the identified topics were qualitatively labelled, and grouped into frames by three of the study's authors (Figure 1). For this task, we adopted six frames from the Science Communication literature (Gerhards & Schäfer, 2010; Schäfer, 2009), as follows:

- **The economic frame** covers discussion about the economic and financial impacts of AI, on both macroeconomic and microeconomic levels. Topics discussed under this frame included *e-commerce*, *venture capital*, and *consumer products*.
- **The scientific frame** includes discussion of the scientific aspects of AI development and application. Examples of topics under this frame included *research output* and *science and technology events*.
- **The entertainment frame** covers discussions of AI in the contexts of popular culture, entertainment, sports, and the arts. *Movies* and *DeepMind playing Go* were the most common topics within this frame.
- **The socio-ethical frame** consists of critical reflection on AI's impact on human society and related ethical issues. Topics grouped under this frame included *AI risks and threats*, and *ethics.*
- **The educational frame** addresses the issue of educational institutions' appropriate response to AI. Topics related to this frame included *school curriculum* and *higher education*.
- **The political frame** refers to discussions of AI in the context of government policies, government regulation, and the geopolitical impacts of AI. For example, China's *national development plan* and *regulation* were related to this frame.

Using two LDA models, we calculated the thetas (θ_f)[4] of the six frames for each article. The θ_f can be interpreted as the prominence of a specific frame in an article. For simplicity's sake, we refer to θ_f as 'theta' in the subsequent sections. Following

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[3] 'Boilerplate' topics are those reflecting general language-usage features.
[4] Our LDA models could generate the topic membership probability θ_t of an article for all topics. These probabilities are mutually exclusive for each article, i.e. $\theta_{t1} + \theta_{t2} + \ldots + \theta_{tk} = 1$. Suppose we grouped t1, t2 and t9 into frame *x* (f_x). The frame membership of an article to frame *x* (θ_{fx}) is equal to the sum of θ_{t1} ,θ_{t2} and θ_{t9} . According to the sum rule, θ_{fx} can be interpreted as the probability of an article falling into t1, t2 or t9.

Griffiths and Steyvers (2004), we constructed the time series of mean theta for each frame, and for each actor group.

[insert Figure 1 here]

3.4 Positioning

In this study, we used sentiment as a proxy for actors' positioning on AI. We conducted a sentiment analysis using the National Taiwan University Semantic Dictionary (NTUSD; Ku et al., 2006). We quantified the sentiment of an article using Relative risk (RR), which is calculated by dividing the number of positive words by the number of negative words plus one, in an article[5]. This metric measures the excess positive sentiment of an article with respect to the negative sentiment.

The accuracy of the dictionary we used can be undermined by its domain-specificity (González-Bailón & Paltoglou, 2015; Ribeiro et al., 2016), so validation was necessary. Therefore, we validated the dictionary against human-coded sentiment (Haselmayer and Jenny, 2016). The validation results indicate that our sentiment metrics captured the sentiment of AI-related content (Appendix B).

4. **Results**

4.1 Standing

In the Chinese public sphere, *PD* represents the voice of the CPC government (Wu, 2014; Zhao, 1998). In contrast, social media such as *WeChat* host a wider range of actors. Therefore, the first research question asked how present different actors were in public discourse about AI on *WeChat*. Through a qualitative study of profiles of *WeChat* public accounts, we identified seven categories of actors. The numbers of accounts and articles were used to measure the prevalence of each actor category.

The first category – *industry actors* – consisted of verified *WeChat* accounts that were affiliated with private companies. This was the most prominent actor category on

[5] In Epidemiology, RR is commonly calculated by the division of two risks. To translate this concept into our sentiment analysis, we calculated the RR by dividing the ratio of positive words by the ratio of negative words. Because the bases of the two ratios are the same, the RR value equals the number of positive words divided by the number of negative words. We added one to the number of negative words to solve the problem of division by zero.

WeChat, making up 46.2 percent of all coded accounts. Among these, technology companies such as Microsoft and Tencent were the most prominent, accounting for 28.7 percent of all profiles. Non-tech companies, on the other hand, made up 17.5 percent of this category. These corporate accounts were comparatively active on *WeChat*, contributing 15,695 articles – more than the sum of articles from all other actors in the sample (Table 1).

Nine point nine percent of accounts were registered by *media organizations*, including newspaper and television stations. These organizations published an average of 17.3 articles per account; this meant that they were considerably less active than industry actors.

Academic actors referred to verified accounts owned by educational or academic research institutions. While universities and their affiliated research institutions represented a large proportion of the academic actors, their accounts constituted only 4.9 percent of the sample. However, with an average of 39.5 articles per account, they were among the most active actors in the AI debate on *WeChat*.

Government and *civil society* actors included government agencies, NGOs, religious groups, and charity organizations. Accounts affiliated with the government and civil society groups constituted 5.2 percent of the sample. The remaining coded *WeChat* profiles either belonged to accounts that were not affiliated with any verified institution, or no longer existed.

[insert Table 1 here]

4.2 Framing

To compare how AI was framed, we calculated the probability of different platforms and actors using specific frames (as explained in Section 3.2). The results are presented in Figure 2.

[insert Figure 2 here]

As the government's mouthpiece (Wu, 2014), *PD* mostly – and unsurprisingly – engaged with the economic and political frames. The vast majority of *PD* articles within these two frames were related to the central government's policies, and promoted narratives around AI's potential to boost China's economic and political power.

On *WeChat*, the economic frame was the most commonly used frame across all actor groups. The second most commonly used frame on this platform was the scientific frame, which included discussion of the scientific and technical aspects of AI development. It is worth noting that the scientific frame was discussed not only by academic accounts, but also by government and industry actors. More precisely, while the academic community published articles about AI-related research output and academic events, government and industry actors' discussions within the scientific frame related mainly to the significance of AI research and the technical aspect of AI-empowered consumer products.

Civil society groups and government institutions were the most active promoters of the political frame on *WeChat,* and their framing of AI followed a similar pattern. For example, both civil society groups and government institutions frequently published content similar to *PD's* news articles – that is, articles that discussed the strategic significance of China becoming an 'AI superpower'. Our analysis also shows that civil society groups were the least engaging actors when it came to discussing the socio-ethical concerns around AI, such as the impact of AI on human society, and the ethical implications of AI development (i.e. the socio-ethical frame). In comparison, academic and media actors were relatively more active in addressing these critical topics.

To compare frames used on *PD* and *WeChat*, we compared each frame's mean theta (Table 2). Our analysis reveals that the economic frame dominated AI discussion on *PD* and *WeChat*, with a mean theta higher than .37 in both cases. The most significant disparity between these two platforms lies in their concern for the socio-ethical frame: while it is the third most common frame on *WeChat*, there is no prevalent topic under this frame on *PD*. The time series plots displayed in Figure 3 and Figure 4 illustrate the temporal evolution of frames; for example, the time series for *WeChat's* socio-ethical frame illustrates that discussion around AI's socio-ethical implications has sharply decreased on this platform in recent years.

The time series analysis also shows that the economic frame was constantly the most prominent on both platforms, although a slight decrease can be observed on *WeChat*. Meanwhile, the prominence of the entertainment frame on *WeChat* and *PD* fluctuated with media events. For instance, the releases of AI-related movies and DeepMind's participation in Go tournaments sharply boosted the number of articles under the entertainment frame.

Meanwhile, the political frame responded to the central government's release of AI-related policies[6], as exemplified by China's 2017 Development Plan for AI. In 2017, the Chinese State Council published an official Development Plan to make China the 'innovation centre for AI' (SCS, 2017), and this received extensive coverage on *PD*. On *WeChat*, a large number of articles were also published by experts to explain the plan's implications and significance for lay citizens.

[insert Table 2 here]
[insert Figure 3 here]
[insert Figure 4 here]

4.3 Positioning

To measure the sentiment in each article, we calculated its relative risk (RR), which indicated whether it showed more positive or negative sentiment. For example, articles about China and Chinese researchers' achievements in AI often scored the highest in RR. In contrast, articles discussing AI's threats to human societies generally received the lowest RR. We first broke down our sentiment analysis results from the *WeChat* data into seven groups of actors, in order to compare each group's RR (Figure 5). The results show that all actor groups discuss AI in a predominantly positive way (all RR> 3.2). In particular, government (RR=5.05), civil society (RR=4.41), and academic institutions (RR=4.16), have the most positive sentiment scores.

A comparison of the sentiment between *WeChat* and *PD* revealed that AI-related content on both platforms showed significantly more positive than negative attitude towards AI (RR= 3.29 & 4.47). Furthermore, time series analysis of the sentiment metrics (Figure 6) indicates that this positive sentiment continues to increase. The Spearman's rank correlations of RR with time are 0.623 and 0.278 for *WeChat* and *PD* respectively, suggesting that the sentiment on both platforms grew more positive over the four years. A particularly high growth rate was observed on *WeChat*. This is in line

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[6] Through an analysis of governmental policy documents, we developed a timeline of key AI-related policies launched in the past four years in China to interpret time series data in context (Appendix C).

with the platform's increasingly prominent discussion about AI's political and technological potency, and its declining focus on its socio-ethical implications. Articles with the lowest RR scores often included the socio-ethical frame, such as discussion around the risks of malfunctioning robots threatening human society. A continuing decrease in the number of articles under this category (as mentioned earlier) helped to boost the overall RR of *WeChat*.

[Insert Figure 5 here]
[Insert Figure 6 here]

5. Discussion

This study investigated the hypothetical role of *WeChat* – as a counter-public sphere in China – in challenging the official state media narratives about AI. Focusing on three dimensions of public discussion – *standing*, *framing*, and *position* – this study compared *WeChat* and *PD's* four year output (2015 to late 2018) of online articles about AI. This comparison showed that *WeChat* played a limited role as a counter-public sphere in challenging *PD's* narratives about the economic and political potency of AI.

The economic interest in the country's AI development is extensive, and highly relevant to various sectors. According to one estimate (Rao et al., 2017), AI could provide a 26 percent boost to China's GDP by 2030, thus making it the world's largest economic beneficiary of AI. This economic motivation behind China's ambitions for AI is well reflected in *PD's* excessive focus on the economic frame. When interwoven political and economic interests combine to materialise China's (so-called) 'AI dream', the resulting positioning of the technology in the media is predictably rosy. As demonstrated by our sentiment analysis, the state media adopts an exceedingly favourable attitude to AI, and this positivity is increasing.

Against the background of this one-sided and overconfident interpretation of AI in the official discourse, a counter-public sphere should present a standing that goes beyond interest groups; promote frames other than the purely economic; and take a position that examines the ethical and social implications of technology more critically.

With regard to *standing*, our analysis of user profiles on *WeChat* reveals a diversity of social actors. These actors included industry institutions, government, academia, the media, and civil society. However, this actor diversity did not necessarily result in an equal distribution of influence: industry actors were still the most prevalent and visible actors on *WeChat*, and they contributed most of the AI-related content.

In the case of *framing*, our findings show that all actor groups were united in their promotion of the economic frame on *WeChat*. One surprisingly active participant in promoting this frame was academia. It is worth pointing out that academic actors' close engagement in discussion of the economic impacts of AI should be interpreted within the context of a growing collaboration between academic institutions and industries. As in other countries, Chinese AI researchers are often involved in both academic and industry sectors (Larson, 2018).

Results from this study reveal that civil society groups served as an amplifier of political and economic frames. This seemingly surprising finding needs to be put into perspective by looking at the relationship between civil society organisations and political institutions in China. As Chinese civil society groups rely on the government for their existence, they need to maintain a close and harmonious relationship with the authorities and, thus, do not challenge them (Dai, Zeng, & Wang, 2017; Hsu & Hasmath, 2014). This explains why civil society groups' framing of AI focused on the economic aspect of its development, thus adopting an almost identical approach to that of the government.

Findings related to the *socio-ethical frame* offer key insights into the assessment of *WeChat's* role as a counter-public sphere. As Wagner et al. (2002: 341) point out, the public is motivated to develop an understanding of new technology. This motivation is not fuelled by its unfamiliarity, however, but by controversies that surround it. Likewise, Goode (2018) also argues that controversy is crucial in stimulating the public's critical reflection on emerging technologies. In the context of the current study, such controversy can be epitomized in the socio-ethical frame. Our analysis shows that *WeChat* did bring public attention to this crucial subject, despite its absence on *PD*. At the same time, the time series analysis indicates that the prevalence of the socio-ethical frame has been declining sharply over the past five years. This trend implies that AI discussions on *WeChat* are becoming increasingly homogeneous, as critical voices weaken.

In the case of *positioning*, our analysis reveals the same growing positive sentiment toward AI on *WeChat* as there is on *PD*. On the one hand, this finding reflects the general openness to, and enthusiasm for digital technology in the wider Chinese society (Lv, 2005; Kostka, 2018). On the other hand, it underscores the need for experts to shake the public out of their complacency.

As previously mentioned, an over-hyped and economy-focused coverage of AI is not unique to Chinese media, but has also been documented in prior studies of Western media (Brennen et al., 2018; Elish and boyd, 2018). What is different in China is the continuing absence of vocal and influential communities that reveal the 'blind spots' within the current AI discourse. In Europe and the US, an expanding league of activists and scholars have been actively advocating for, and raising awareness of, ethical, accountable, and sustainable AI development[7]. In China, the responsibility to foster a similar movement is now on the shoulders of researchers, especially those with social science and humanities backgrounds.

6. Conclusion

In Cath et al.'s (2018) vision of a 'good AI society' for the US, EU, and the UK, AI's power should be fully steered towards promoting the public good. In the case of China, what constitutes the public good, and the way it can be delivered, relies on a rational and inclusive counter-public sphere. In such a sphere, grassroots discourse challenges official doctrines. Existing literature often depicts new communication technologies in China as a counter-public sphere that competes against the heavily regulated mainstream media (Lee, So, & Leung, 2015; Sima, 2011; Rauchfleisch & Schäfer, 2015). However, our study suggests that social media's role as a counter-public sphere in AI discourses is minimal.

The lack of a counter-public sphere to influence China's vision and strategies related to AI can be detrimental. When an entire nation – from academia to the business sphere and from the government to civil society – is collectively and uncritically working on AI's rapid expansion, the consequences can be severe. As demonstrated by the recent CRISPR babies scandal in China (Kuo, 2018), when ambition overrules regulation and

[7] Some sample institutions include The Institute for Ethical AI & Machine Learning (UK); The AI Now Institute (US); and The Future of Life Institute (US).

when self-interest overrules ethical consideration, technological ‘innovation’ can have profound consequences. Similarly, in the case of China’s AI development, if the current trajectory continues to be driven solely by political and economic interests, the results can have irreversibly devastating consequences.

The future trajectory of China’s AI dream remains hard to predict. Our analysis shows that the official rhetoric about AI is highly responsive to external events. A single policy change from the central government can drastically alter the AI sector. The powerful influence of the Chinese government can be a double-edged sword. On the one hand, the official AI discourse exercises a hegemonic power over public opinion on the issue, thus limiting healthy debate and critical reflection. On the other, this centralised power grants Chinese authorities a certain responsive advantage over its Western counterparts when it comes to quickly and effectively implementing policies. For example, if the government saw an advantage in approaching AI development with more caution and critical reflection, it could, in theory, quickly alter its trajectory and implement policies to reflect this new approach.

The shift mentioned above is not impossible. In Europe and the US, transparency and accountability are held as two fundamental values to guide policymakers’ AI schemes (Cath et al., 2018). If China wants to become a real ‘AI superpower’ and compete against these two powers, it has to catch up in, even lead, the development of a substantive ethical framework. As this paper is being written, the US-China trade war is still unfolding. One important lesson for China to learn from the US sanctions on its technology products is that both China and its technology sector have to work to rebuild the West’s trust. Setting a high ethical standard with regards to transparency and accountability might be an effective starting point.

There are limitations to this study. First, Chinese social media are heavily regulated, and criticism of the central government is heavily censored. Some AI-related articles on *WeChat*, for example, might have been censored. To investigate this possibility, we used an archive of censored *WeChat* posts – *FreeWeChat* (McDevitt, 2016) – to search for deleted posts on the AI topic. This search (in December 2019) returned only four articles that contained the term ‘artificial intelligence’ (□ □ □ □), and none of these discussed AI as its main topic. Furthermore, earlier research of online censorship in China suggests that discussion of non-politically sensitive topics is less prone to censorship (Fu, Chan, & Chau, 2013; King, Pan, and Roberts, 2014; Zeng, Chan, Fu, 2018). While we cannot entirely eliminate the possibility that articles might have been censored, both our investigation of archived deleted social media posts and previous studies, suggest that censorship has a limited impact.

Second, we chose a dictionary-based approach to develop a preliminary sentiment profile of the 140,000 articles collected and analysed in this study. Even though we employed manual coding for validation, dictionary-based approaches to assessing sentiment still have certain shortcomings, such as the over-simplification of human perception of emotion in a text (González-Bailón & Paltoglou, 2015; Ribeiro et al., 2016; Puschmann, 2018). Future studies should consider conducting sentiment analysis on this large data set with machine learning tools, which use human-coding to train sentiment assessment algorithms (González-Bailón & Paltoglou, 2015).

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Appendix A: codebook for actors

[insert Table 3 here]

Appendix B: Validation of NTUSD

We randomly selected 500 articles from our WeChat and PD corpora. We restricted our inclusion criteria to articles less than 1500 words in order to reduce the cognitive loading of the crowd-coding task (Mohammad & Turney, 2010).

We used the crowdsourcing platform – Figure Eight (figure-eight.com) – for this task. Participants understand Simplified Chinese and English. They were asked to code each article's sentiment using a 4-point ordinal scale. Figure 7 shows a screenshot of the crowd-coding screen.

[insert Figure 7 here]

For each article, three coding results from different participants were collected. We calculated the human-coded sentiment scores by averaging the result from three coders. Figure 8 shows the scatterplot of human-coded scores and relative risk metrics derived from NTUSD. A regression line is also displayed.

The correlation between the two variables is statistically significant (Pearson's correlation: 0.238, $p < 0.0001$). Because 'off-the-shelf' sentiment dictionaries are commonly used without revalidation, there is no established threshold of correlation for accepting a dictionary. However, by comparing our result with a handful of priors attempts to revalidate off-the-shelf dictionaries (Haselmayer & Jenny, 2016; Boukes et al., 2019), we can argue that our validation result is acceptable. As the correlation is statistically significant, we deem the criterion validity of our measurement to be adequate.

[insert Figure 8 here]

Appendix C Timeline of Chinese government's AI policies

[insert Table 4]

Tables

Table 1. Summary of actor categories.

Actor categories		Accounts (in %)	Number of articles	Average number of articles per account
Industry	technology companies	28.7 n=316	12,984	41.1
	non-tech companies	17.5 n=192	2,711	14.1
Media organizations		9.9 n=109	1,881	17.3
Academic		4.9 n=54	2,133	39.5
governmental institutions		3.6 n=40	411	10.3
Civil Society		1.6 n=18	251	13.9
non-institutional accounts		30.7 n=338	4,433	13.1
Other		3.0 n=33	526	15.9

Table 2. *Framing in AI articles – Mean theta (95% Confidence Interval)]*

	WeChat (n = 124,711)	PD (n = 20,666)
Economic frame	0.376 (0.375 to 0.378)	0.398 (0.0296 to 0.402)
Scientific frame	0.165 (0.164 to 0.166)	0.116 (0.114 to 0.119)
Socio-ethical frame	0.0878 (0.0871 to 0.0886)	
Entertainment frame	0.0823 (0.0816 to 0.0830)	0.0866 (0.0845 to 0.0888)
Political frame	0.0804 (0.0797 to 0.0810)	0.135 (0.132 to 0.137)
Educational frame	0.0740 (0.0734 to 0.0745)	0.0308 (0.0296 to 0.0321)

Table 3. Codebook for actors

Category		Description	Example
Media organisation		The account explicitly indicates that the account is associated with a media organisation, including newspapers, magazines, television, and new media companies. Individuals authenticated with these media organisations were also coded under this category.	• Qinhuangdao Daily • Beijing Youth Weekly
Industry	technology / IT company	The account explicitly indicates that it is associated with a technology or an IT company. Individuals authenticated with these companies were also coded under this category.	• TenCent • Microsoft_AI_Toutiao
	non-tech companies	The account explicitly indicates that it is associated with non-tech and non-media institutions. Individuals authenticated with these companies were also coded under this category.	• Red Star Macalline • Guotai Junan Securities
Academic		The account explicitly indicates that it is associated with an academic or educational institution Individuals authenticated with these institutions were also coded under this category.	• Tsinghua University • Chinese Academic of Science
Governmental institutions		The account explicitly indicates that the account is associated with a central or regional governmental body. Individuals authenticated with these institutions were also coded under this category.	• Jiang Yin Municipal Commission of Economy and Informatization, • SME Bureau of Chongqing
Civil Society		The account explicitly indicates that the account is associated with civil society organisations, including NGOs, charitable organizations, religion-based organizations, and professional associations. Individuals authenticated with these organizations were also coded under this category.	• Human Resource Non-Governmental Organization, • Shanghai Jiading Fanxiejiao Association
Non-institutional		Accounts without authentication as an institution.	• Renwu story
Other		Accounts’ associated with users other than the categories listed above, or accounts that no longer exist.	• FilmHorn, • Leifeng Wang

Table 4. Timeline of Chinese government's AI policies

Publish Time	Issuing Body	Policy Title
2015 May	State Council	Made in China 2015
2015 July	State Council	Guiding Opinions of the State Council on Vigorously Advancing the "Internet Plus" Action
2016 March	National Congress	Outline of the 13th Five-Year Plan for the National Economic and Social Development of the PRC
2016 April	MI, NDRC, MF	Robot industrial developing plan(2016-2020)
2016 May	NDRC, MST, MIIT, CCAC	'Internet Plus' Artificial Intelligence Three-Year Action Implementation Plan
2016 July	MST	Circular of the State Council on Issuing the National Scientific and Technological Innovation Planning for the 13th Five Years
2016 September	MIIT, NDRC	Innovation and development of intelligent hardware industry initiative (2016-2018)
2016 November	State Council	the 13th Five-Year National Plan for the Development of Strategic Emerging Industries
2017 March	12th NPCPRC	Report on the Work of the Government 2017
2017 July	State Council	Notice of the State Council on Issuing the Development Plan on the New Generation of Artificial Intelligence
2017 October	CPC	19th CPC National Congress
2017 December	MIIT, MST	Three-Year Action Plan for Promoting Development of a New Generation Artificial Intelligence Industry (2018–2020)
2018 March	13th NPCPRC	Report on the Work of the Government 2018

Notes: PRC: the People's Republic of China
MI: Ministry of Industry
NDRC: National Development and Reform Commission
MF: Ministry of Finance
MST: Ministry of Science and Technology
MIIT: Ministry of Industry and Information Technology
CCAC: Office of the Central cyberspace affairs commission
NPCPRC: National People's Congress of the People's Republic of China

Figures

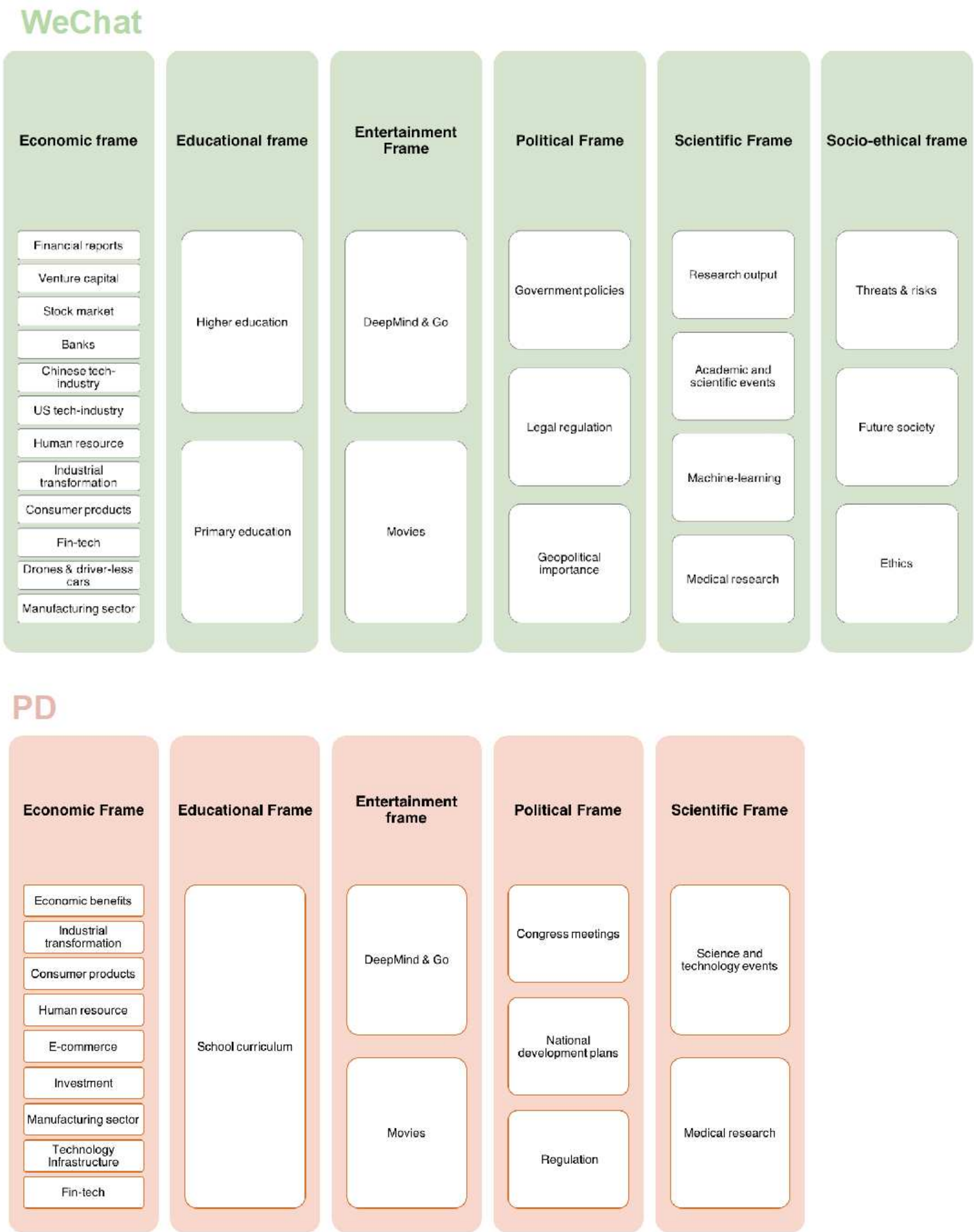

Figure 1. Topic arrangement of *WeChat* and *PD* articles.

Figure 2. Average theta for each frame of AI articles published by each actor group.
(Note: x-axes are log-transformed)

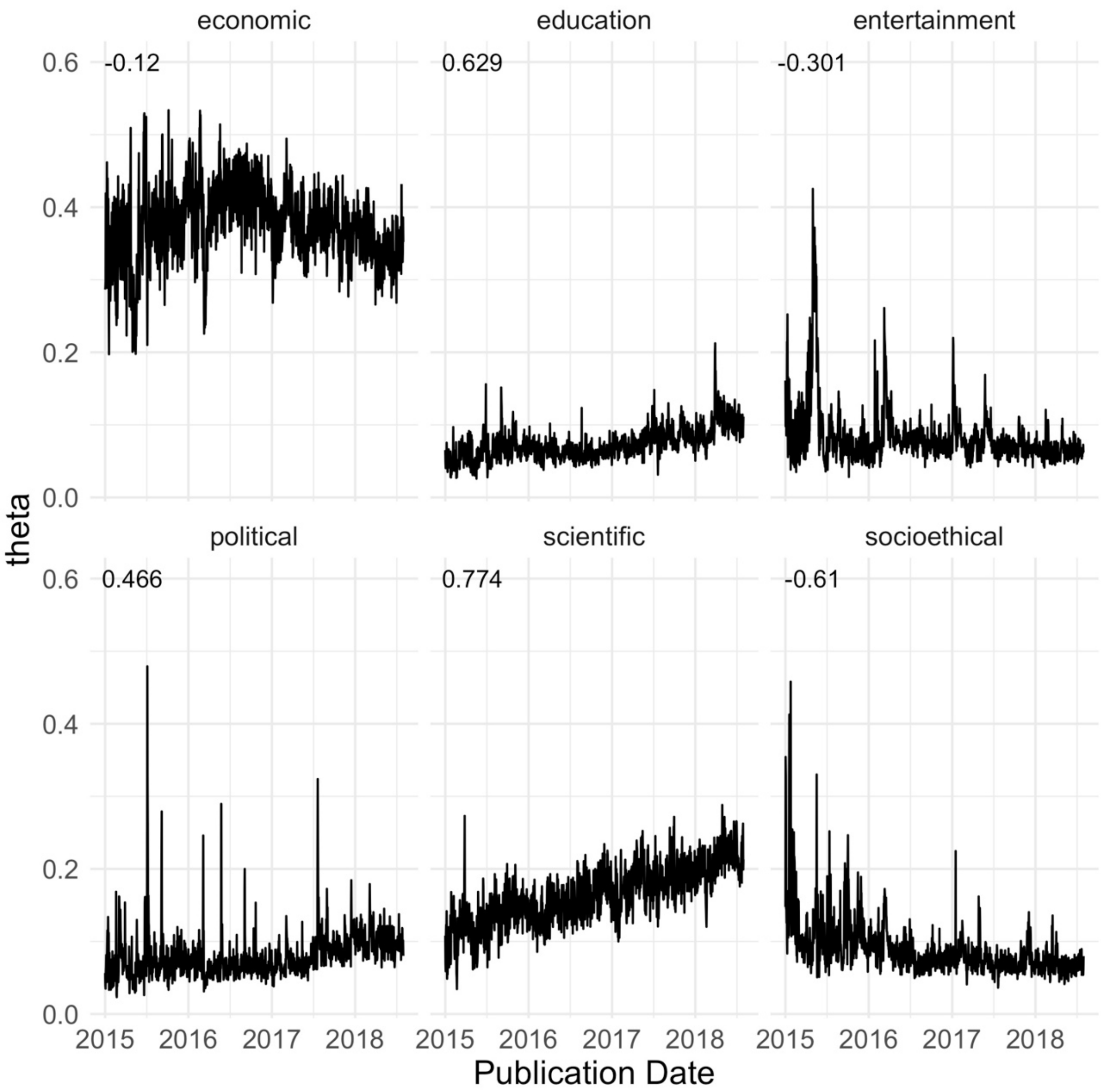

Figure 3. Time series of daily mean theta for each frame of AI articles from *WeChat* (Note: The numbers on the upper-left corner are Spearman's rank correlation coefficients between theta and time).

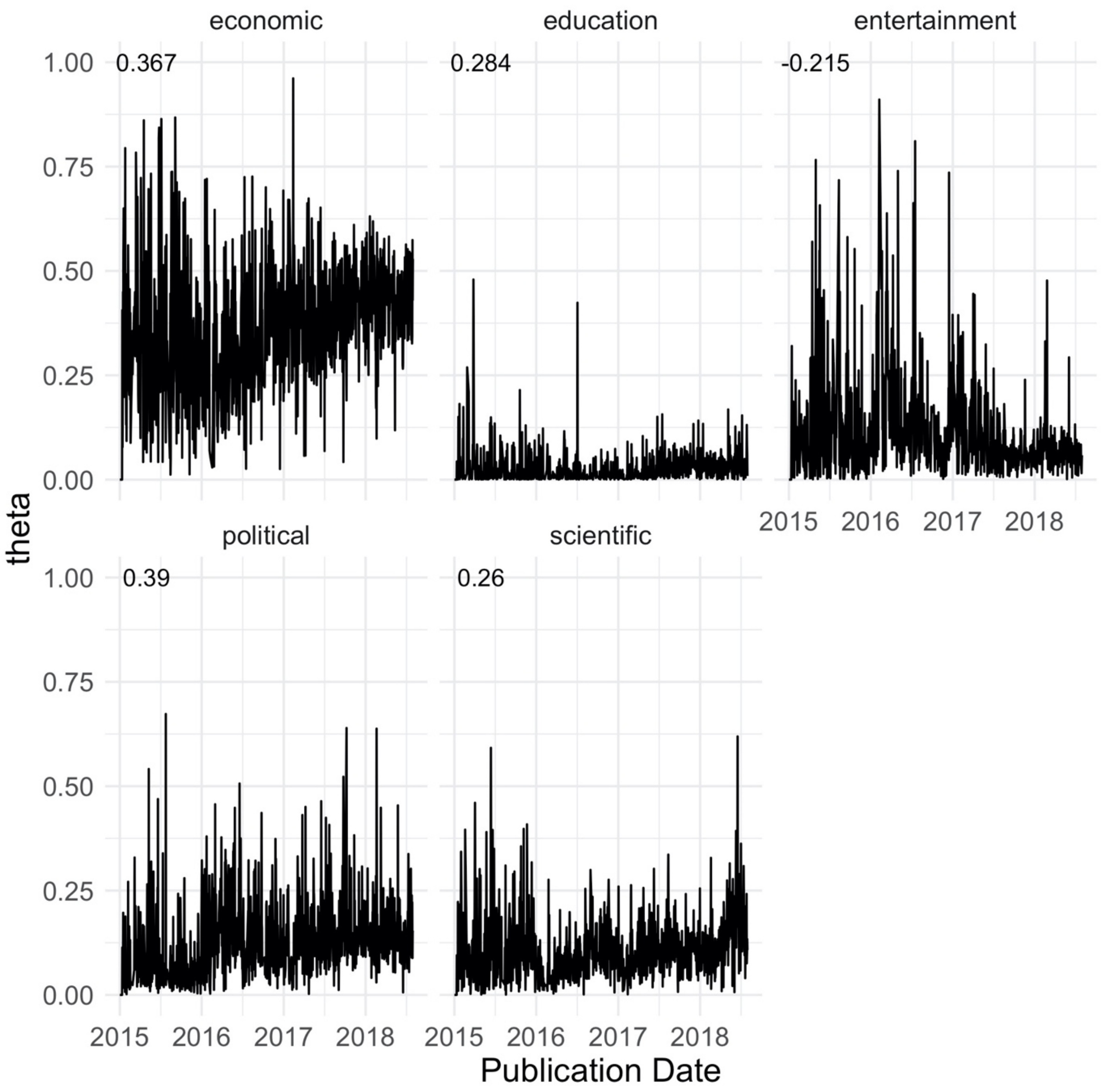

Figure 4. Time series of daily mean theta for each frame of AI articles from *PD* (Note: The numbers on the upper-left corner are Spearman's rank correlation coefficients between theta and time).

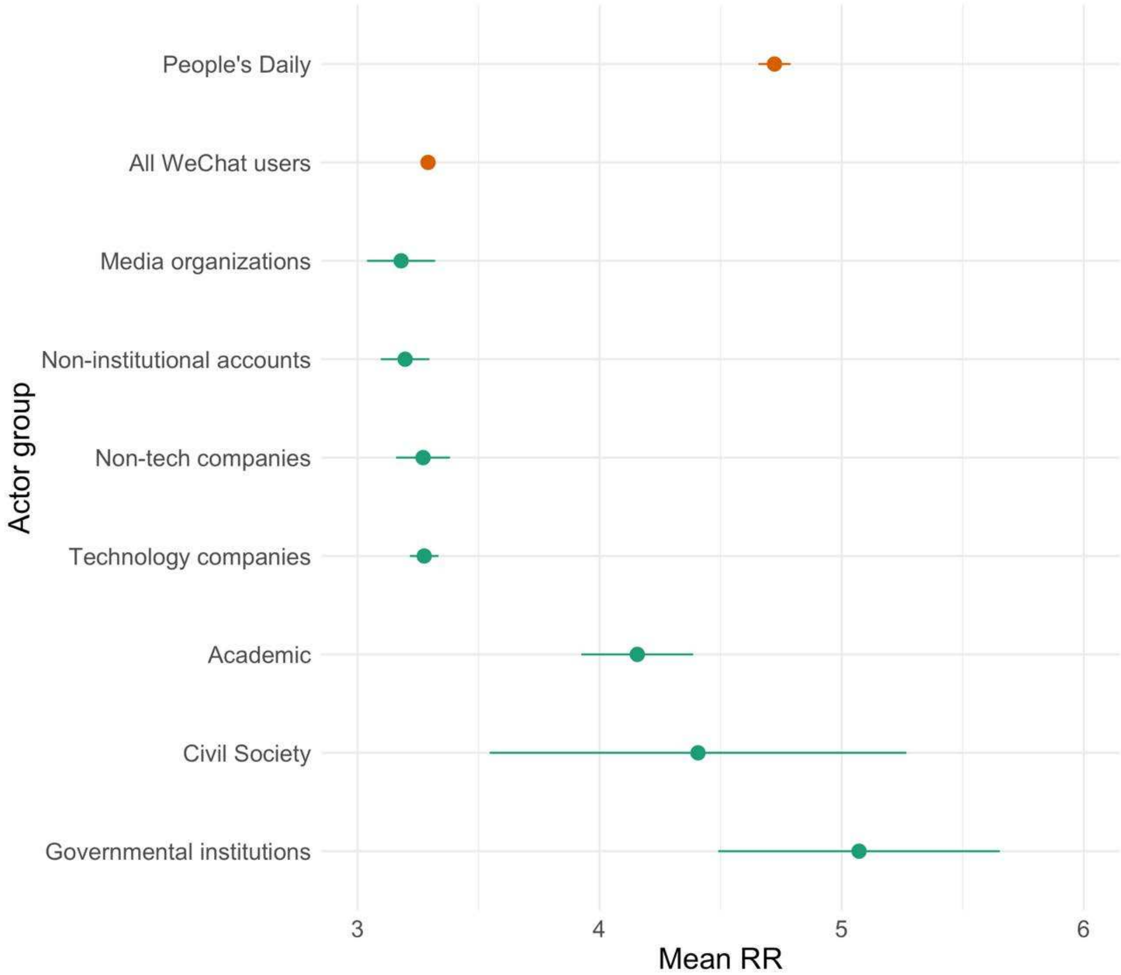

Figure 5. Mean sentiment score (RR) of AI articles from actor groups (Note: The bands around the mean values are 95% confidence intervals).

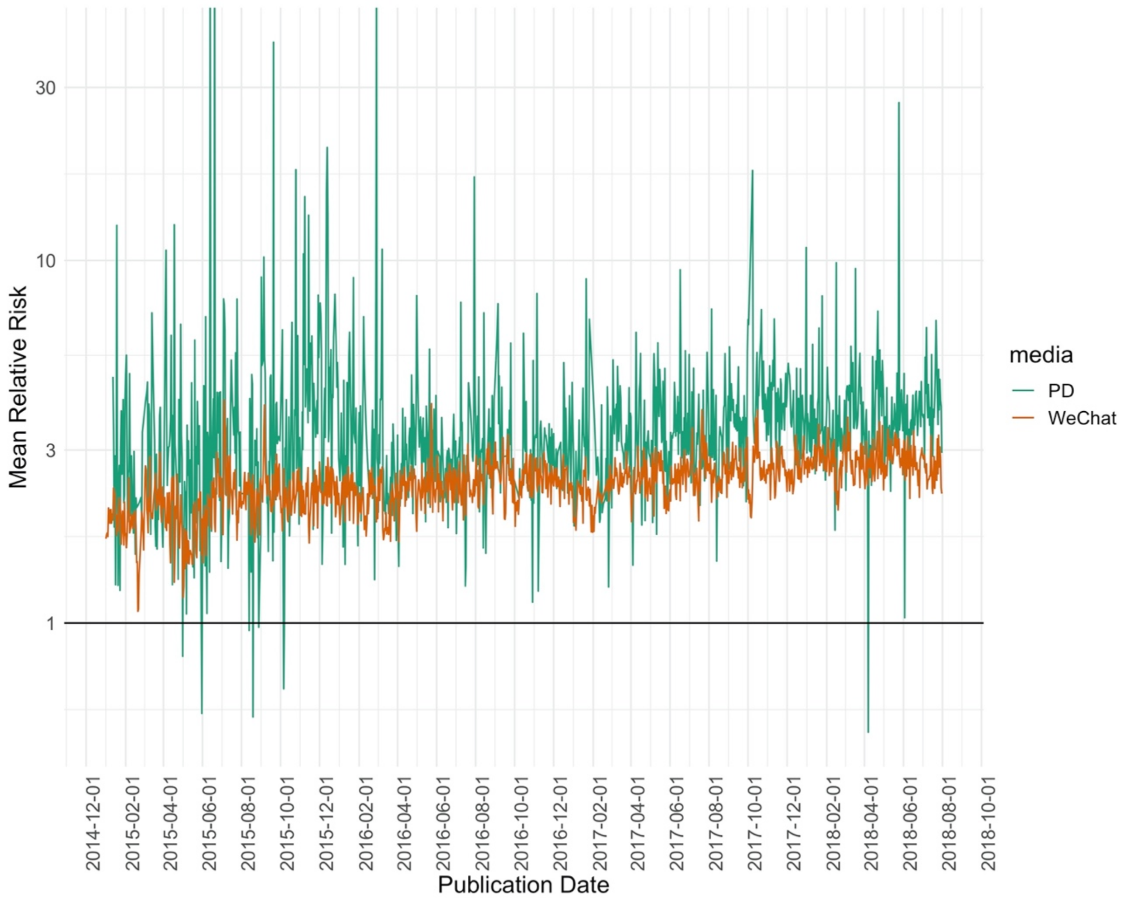

Figure 6. Daily mean RR of AI articles on *PD* and *WeChat*.

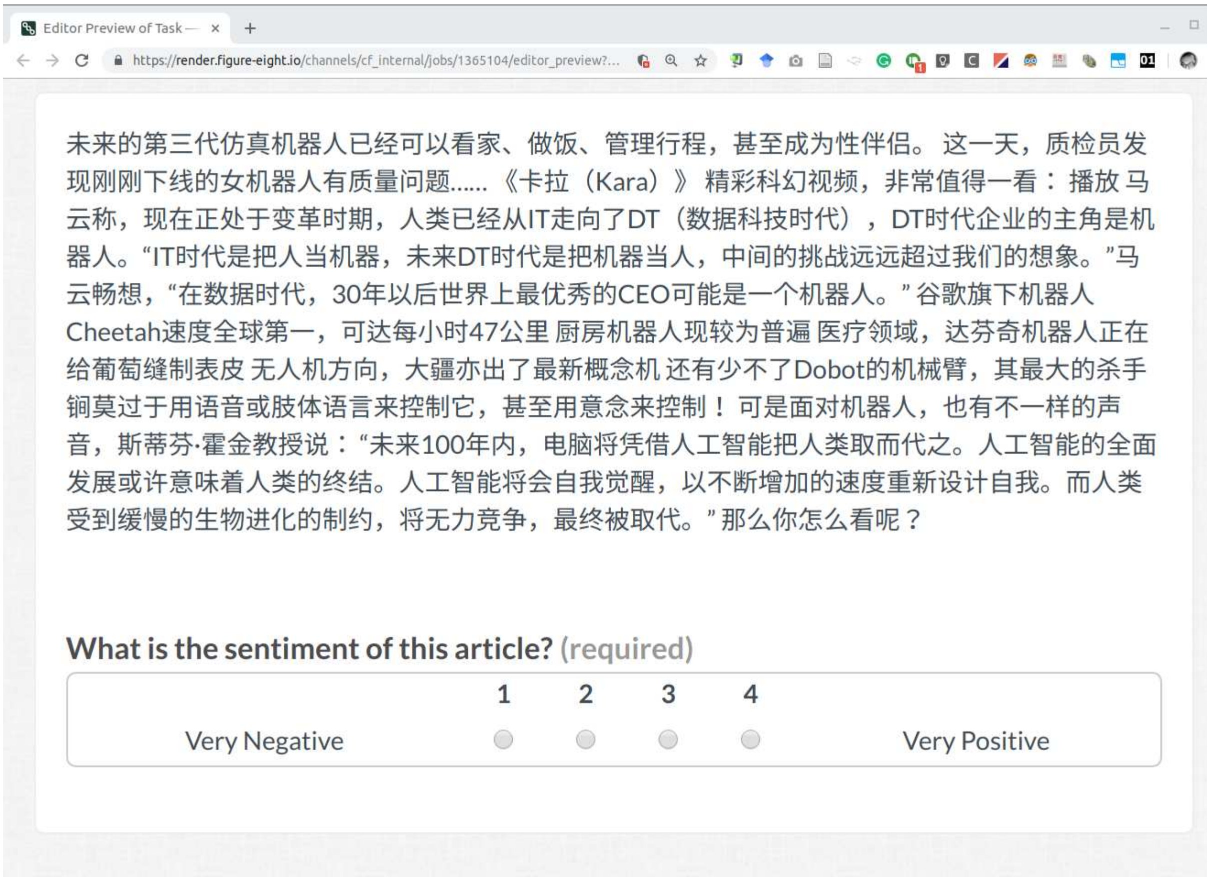

Figure 7. Screenshot of an example task.

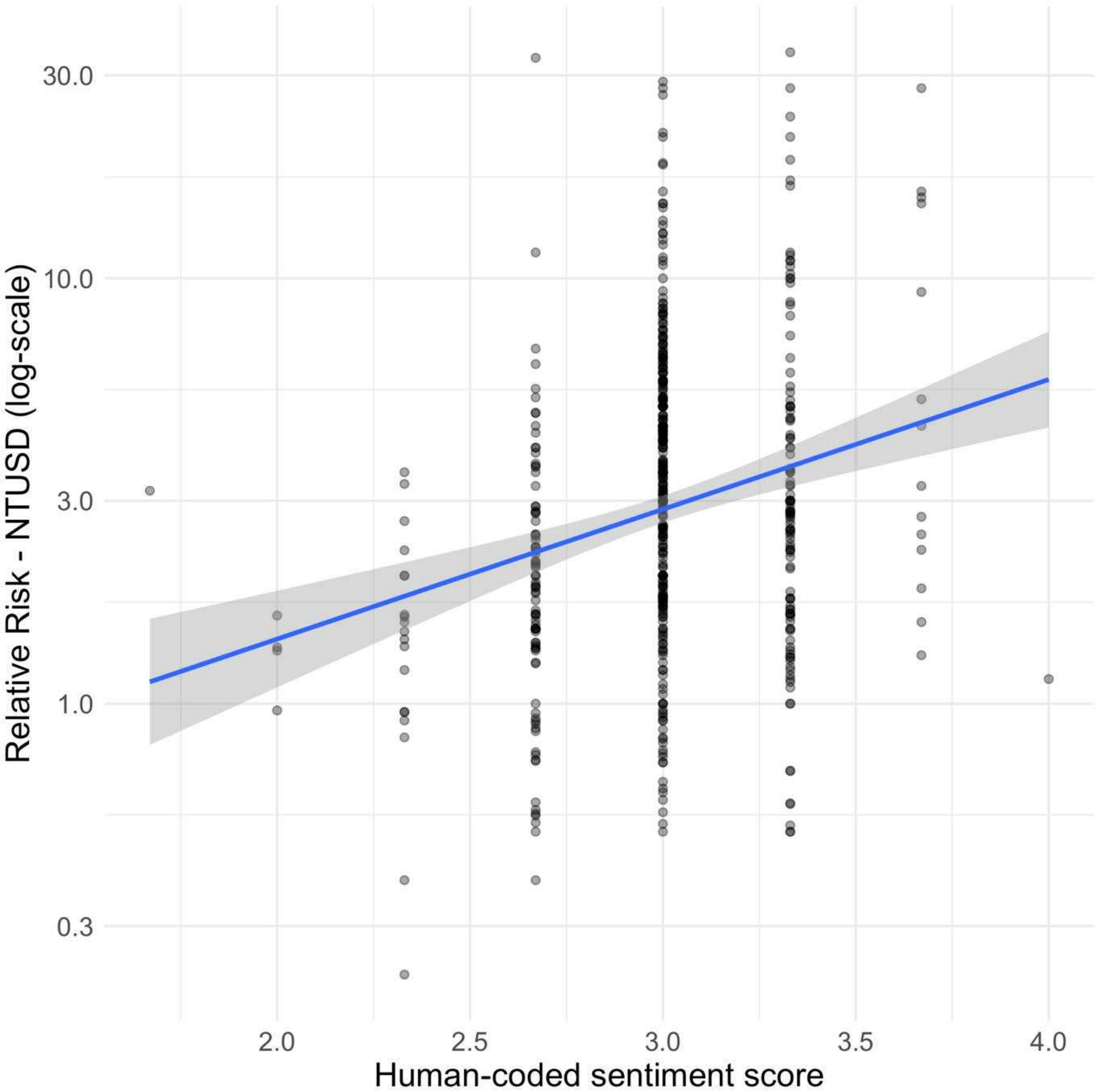

Figure 8. Hand-coded sentiment vs NTUSD